Leveraging BWIM System Traffic Data for Long-Term Structural Health Monitoring of Highway Bridges

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Abstract

This study investigates utilizing raw strain measurements from Bridge Weigh-In-Motion (BWIM) systems for long-term structural health monitoring of highway bridges. Using one year of continuous traffic data collected from an instrumented bridge on the Trans-Canada Highway in New Brunswick, the research demonstrates that select classes of vehicles can serve as consistent probes of bridge response, even without prior knowledge of vehicle weights.

Local deck strain signals were processed to detect vehicle presence and axle configurations using a combination of thresholding, peak detection, and a supervised Support Vector Machine (SVM) classifier. Initial analyses focused on 7-axle trucks; however, due to observed variability in their strain responses, a

more refined selection of log trucks—a specialized vehicle class with highly uniform configurations—was undertaken. The results showed that log trucks produced strain responses with significantly lower variability, confirming the critical role of meticulous vehicle selection in achieving reliable monitoring. Temperature effects were also evaluated by correlating monthly average strain responses with ambient temperature data. A moderate and statistically significant positive correlation was observed, highlighting the necessity of accounting for environmental factors when interpreting structural response trends over time.

Overall, the findings suggest that BWIM installations, traditionally used for traffic weight estimation, can be repurposed for efficient, continuous bridge monitoring. Strategic selection of vehicle types and environmental correction procedures are essential for maximizing the reliability of such monitoring frameworks. This approach offers a scalable, low-cost alternative to conventional Structural Health Monitoring (SHM) systems through utilizing existing BWIM systems.

Introduction

Background and Motivation

Bridges are critical links in transportation networks, and continuous monitoring of their condition is crucial for safe, efficient operation[1]. Structural health monitoring (SHM) of highway bridges has gained increasing attention in recent years as aging infrastructure and heavy traffic raise safety concerns. Modern SHM systems use various sensors (strain gauges, accelerometers, tiltmeters, etc.) to continuously measure bridge responses and detect deterioration [2,3]. However, the high cost of long-term sensor installations means SHM is typically limited to major bridges[4]. Hence, cost-effective strategies are needed to monitor the vast inventory of short-span highway bridges.

One promising solution is Bridge Weigh-In-Motion (BWIM) systems. BWIM uses an instrumented bridge to measure the axle and gross weights of vehicles as they cross, turning the structure into a scale without interrupting traffic[4]. Originally developed in the 1970s to weigh trucks in motion[5], BWIM technology is now widely used for traffic monitoring and weight enforcement. Each truck crossing yields a characteristic strain response in the bridge, but this rich data is typically used only to calculate vehicle weights.

This study proposes to unlock the untapped SHM potential of BWIM data. Research suggests that the same strain measurements used for BWIM can serve as long-term indicators of structural behavior. By crowdsourcing data from trucks that regularly cross the bridge – especially those with similar configurations – structural response signatures can be tracked over time. Such signatures can indicate stiffness loss or other deterioration. Indeed, studies have shown that influence lines derived from normal traffic can detect subtle bridge changes (e.g., after bearing replacement)[4]. Leveraging an existing BWIM installation in this way is novel, as it enables continuous, low-cost monitoring without extra sensors[6]. In the present work, a permanent BWIM system installed on a 33 m single-span prestressed concrete girder overpass (Route 2 near Sackville, New Brunswick) provides continuous crowdsourced truck data to demonstrate the feasibility and accuracy of this dual-use approach.

Literature Review

Structural health monitoring (SHM) of highway bridges has gained increasing attention in recent years as aging infrastructure and heavy traffic raise safety concerns. Modern SHM systems use various sensors (strain gauges, accelerometers, tiltmeters, etc.) to continuously measure bridge responses and detect deterioration [2,3]. However, the high cost of long-term sensor installations means SHM is typically limited to major bridges[4]. Hence, cost-effective strategies are needed to monitor the vast inventory of short-span highway bridges.

Bridge Weigh-In-Motion (BWIM) systems were originally developed as an alternative to pavement WIM to measure truck loads continuously on highway bridges. Moses showed in the 1970–80s that with a known influence line one can invert measured strains to estimate vehicle axle weights and velocities[5]. Over time, BWIM technology has evolved with improved instrumentation and algorithms. For example, modern systems employ high-speed strain gauges or fiber-optic sensors to capture bridge deformations [7,8]. BWIM data is primarily used for traffic load monitoring and management. The information obtained has been applied in a wide range of practical areas, including screening for overweight trucks (enforcement), gathering traffic statistics for planning purposes, and calibrating bridge and pavement design models to reflect actual loading conditions[9]. B-WIM systems offer benefits such as durability, portability, and easy installation, while not only estimating vehicle weight but also providing valuable structural data for bridge evaluation, thereby overcoming the limitations of pavement-based WIM systems[10].

More recently, researchers have explored using BWIM data not only for traffic metrics but also for structural assessment. Because BWIM sensors measure actual strain responses under known loads, they inherently capture the bridge's mechanical behavior. BWIM technology can augment traditional structural health monitoring (SHM) systems: a BWIM installation inherently measures bridge deflections or strains (as part of weighing), thus yielding structural information almost as a by-product [11]. Several methods have been proposed to detect anomalies using BWIM data. Cantero *et al.* introduced a "virtual axle" concept where deviations in the estimated axle weights from the bridge system reveal damage[12]. Gonzalez and Karoumi developed a two-stage algorithm using BWIM-derived load positions and magnitudes together with bridge vibration to classify damage states[13].

In practical terms, a BWIM system continuously records strain histories for each heavy vehicle crossing, from which one can reconstruct the bridge's bending or moment influence line over time. By tracking the IL over weeks or months, subtle shifts can be detected that may indicate degradation. This approach effectively repurposes the BWIM sensors (strains/deflections) for SHM, allowing the same hardware to serve dual purposes [4,14]. These advances indicate that BWIM raw data – beyond simple weights – can directly feed SHM models and algorithms, especially when integrated with other sensor data (accelerations, deflections) for comprehensive monitoring[6].

When using raw BWIM data for SHM, certain practical considerations arise. First, not all vehicles produce equally useful signals. Small cars or lightly loaded trucks induce negligible bridge response compared to heavy trucks. Second, long-term variation in ambient conditions must be accounted for. As noted, thermal expansion can dominate measured strains. State-of-the-art SHM practice therefore incorporates temperature compensation[3].

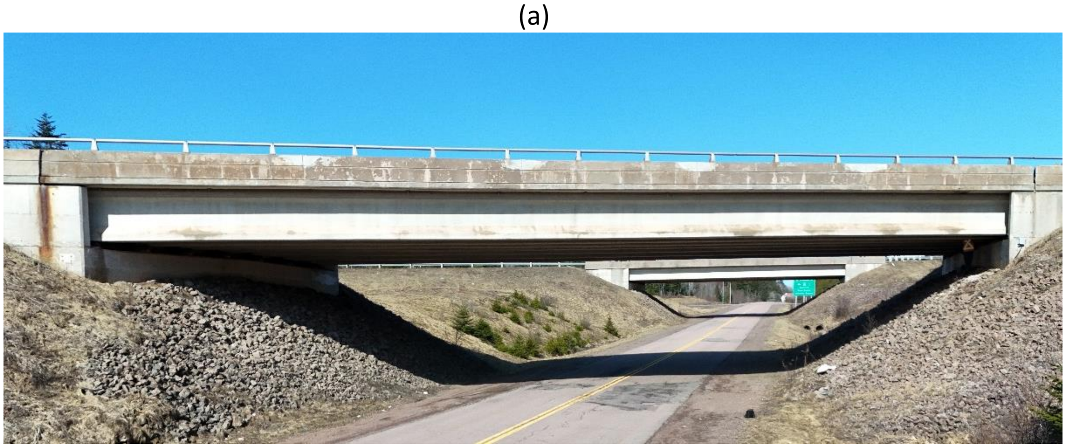
This study aims to investigate the potential application of BWIM data for structural health monitoring (SHM) from a new perspective. By systematically collecting data from trucks that regularly cross the bridge—particularly those with similar configurations—the evolution of the bridge's structural response over time can be monitored. Variations in the observed responses may indicate stiffness loss or other forms of deterioration. The approach proposed in this study is novel in that it leverages an existing BWIM system to enable continuous, cost-effective monitoring without requiring additional sensor installations. To demonstrate the feasibility and accuracy of this dual-purpose approach, continuous truck data collected from a permanent BWIM installation on a 33-meter single-span prestressed concrete girder overpass located on Route 2 near Sackville, New Brunswick, is utilized.

Case Study Bridge

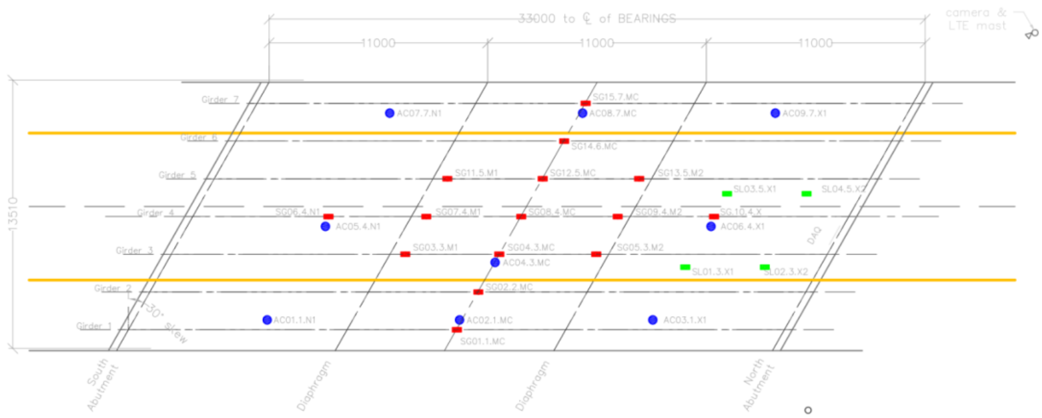
Data for the present study were obtained from a bridge instrumented in partnership with the New Brunswick Department of Transportation and Infrastructure (NBDTI). The structure, located along Route 2 (TransCanada Highway) near Sackville, New Brunswick, serves the westbound traffic and consists of a single-span slab-on-girder overpass. The bridge spans approximately 33.0 meters and has a total width of 13.5 meters. Its superstructure comprises a 200 mm thick concrete deck, which is supported by seven simply supported, prestressed concrete girders (NBDOT Type-1) resting on elastomeric bearings.
In fall 2022, the bridge was equipped with an integrated BWIM-SHM (Bridge Weigh-In-Motion – Structural Health Monitoring) system. This instrumentation setup includes nine PCB 625B02 accelerometers affixed to the underside of the slab, along with an area-scan camera positioned near the exit abutment to provide continuous, time-synchronized photographic records of the traffic flow (Figure 1).

Figure 1 Case study bridge (L930): plan view (a), side view (b), sensor layout (c).

(a)



(b)



(c)

<u>Data Collection and Preprocessing</u>

Sensor data are acquired at a sampling frequency of 1 kHz, enabling the accurate evaluation of one-sided spectral content up to 500 Hz without the risk of aliasing, in accordance with the Nyquist-Shannon sampling criterion. For the purposes of this study, global girder strain and local deck strain measurements collected between 7:00 AM and 5:00 PM daily — corresponding to daylight hours to allow for concurrent use of image data — were analyzed. The dataset covers a continuous 12-month period from September 2023 to August 2024.

Vehicle Detection and Identification

<u>Vehicle Detection Using Local Deck Strain Signals</u>

In this study, local deck strain signals were utilized for vehicle detection. A thresholding approach was applied to the moving average of the preprocessed strain signal recorded by the first sensor positioned beneath the primary cruising lane. The threshold level was set slightly above the background noise to suppress inactive regions while preserving signal intervals corresponding to vehicle presence. These identified intervals were subsequently processed to locate axle peaks.

<u>Axle Configuration Determination</u>

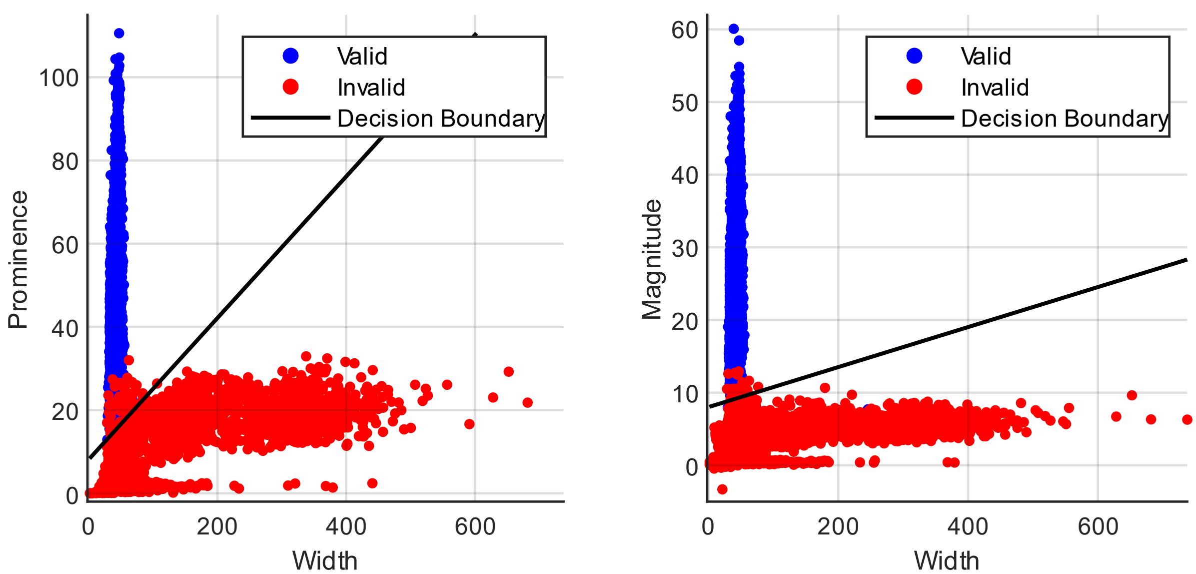
The passage of vehicle axles generates distinct sharp peaks in local deck strain signals, particularly when the vehicle’s wheel path does not align directly over the girders. This characteristic forms the basis of axle configuration detection in Bridge Weigh-In-Motion (BWIM) systems. In the present study, the instantaneous speed of each vehicle was estimated by analyzing the time lags between signals recorded by strain sensors installed at known locations along the driving lanes. Given the measured time delays, the known spatial distances between sensors, and the data acquisition system's sampling frequency, the physical axle spacings were calculated.

Peak Parameters

While identifying axle-induced peaks is straightforward through visual inspection, automated peak detection requires robust algorithmic strategies. Two primary challenges arise: (a) the number of axles per vehicle is unknown a priori, and (b) local strain signals may include non-axle-related peaks.

To address this, a supervised classification approach was developed. A manually curated dataset of vehicle passages was created, with each vehicle's axle count verified through corresponding event images. For each recorded event, valid and invalid peaks were identified, and peak characteristics—namely, magnitude, width, and prominence—were extracted using MATLAB's findpeaks function. These features formed the input to a Support Vector Machine (SVM) classifier with a linear kernel. The classifier was trained using 70% of the labeled dataset, with five-fold cross-validation employed to mitigate overfitting risks. Figure 2 illustrates the distribution of peak parameters and the SVM decision boundary. The resulting cross-validated classification accuracy reached 99%.

Figure 2. Local strain peak parameters, and linear SVM decision boundary



Selection and Screening of 7-Axle Trucks

Among the various vehicle types crossing the bridge, 7-axle trucks were selected as a representative vehicle class for this study. These trucks exhibited consistent and repeatable strain responses, making them suitable candidates for structural monitoring applications. The trained SVM classifier was applied to detected events to identify occurrences corresponding to 7-axle trucks. Each identified event was manually validated using captured camera images to confirm both the number of axles and the isolation of the vehicle (i.e., ensuring no concurrent presence of other vehicles on the bridge during the event).

Once the pool of isolated 7-axle truck events was established, the vehicle speeds were computed via cross-correlation of strain signals from two longitudinally spaced sensors. Assuming constant vehicle velocity across the bridge span, the start and end times for each crossing event were estimated. Minor uncertainties in start/end time estimation were deemed negligible and did not affect critical features such as maximum strain magnitude or integrated strain response.

Extraction of Global Strain Response

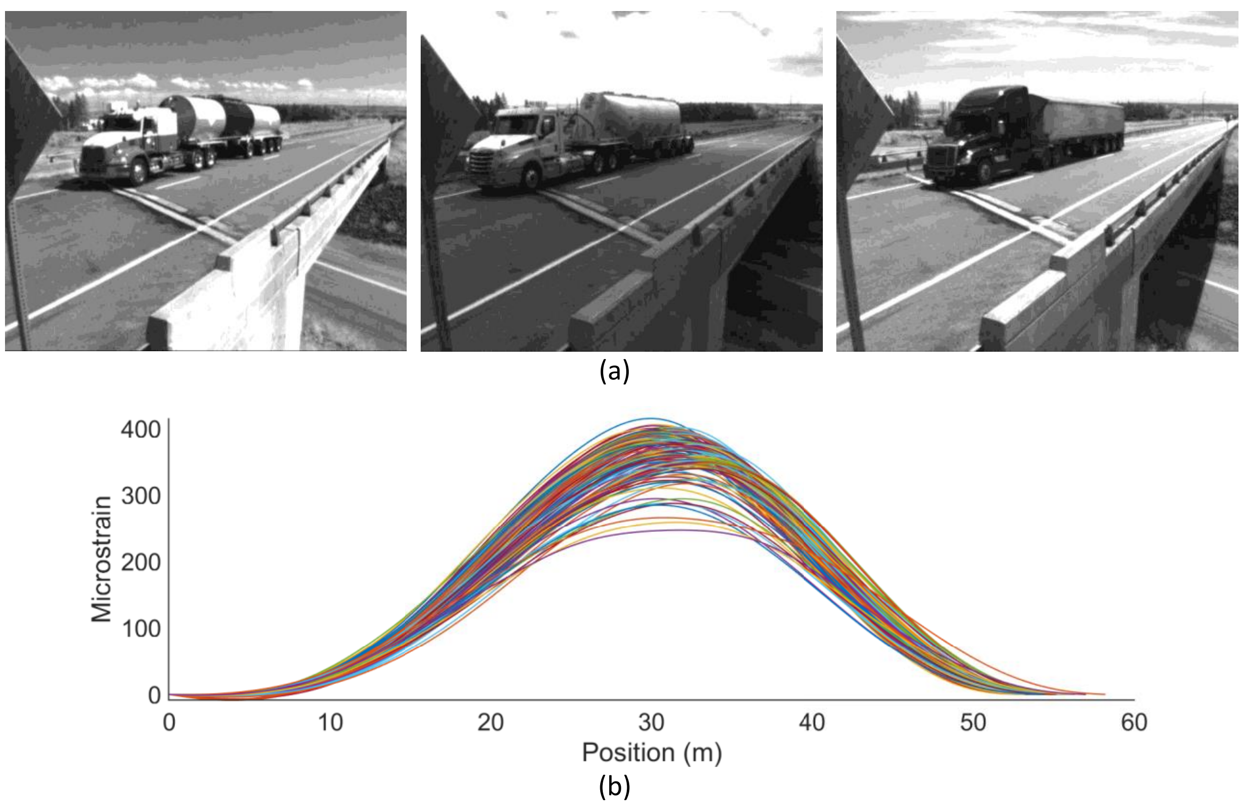
To characterize the global structural response for each selected vehicle event, the static bending strain profile of the bridge was reconstructed. This was achieved by summing the low-pass filtered strain signals (filtered at 0.5 Hz to isolate static response components) from all girder-mounted sensors throughout the event duration. Two key response features were extracted for monitoring purposes: (1) the maximum strain magnitude, and (2) the area under the strain-position curve, representing the cumulative strain distribution along the bridge span.

Results and Discussion

Analysis of Vehicle Type Selection

In the initial phase of the study, all isolated single-vehicle events corresponding to 7-axle trucks were extracted for the month of June 2024, yielding a total of 137 identified trucks. Figure 3 presents representative photographs of these vehicles along with the corresponding girder strain responses for comparison.

Figure 3. 7-Axle trucks isolated in June 2024: sample truck photos (a), girder strain response (b)



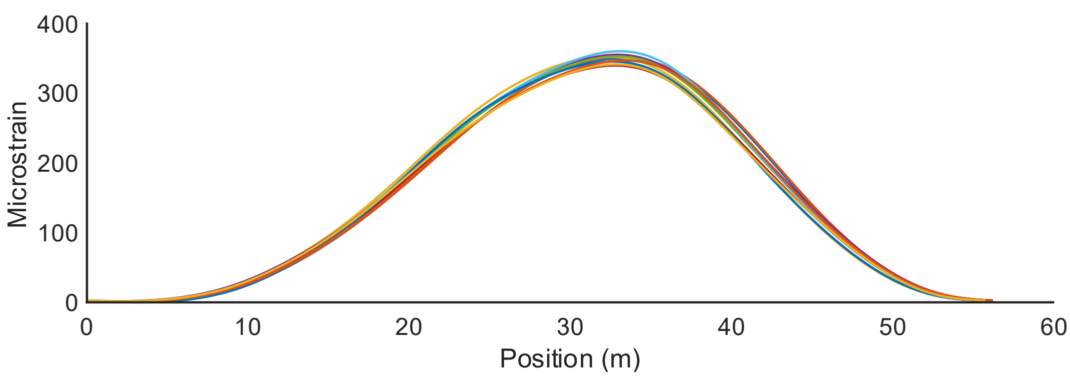
As illustrated in Figure 3, significant variability exists among the strain responses of the 7-axle trucks. Across the 137 vehicles, the average maximum strain was found to be 366.22 microstrains, with a coefficient of variation (CV) of 8.6%. Similarly, the average area under the strain response curves was calculated as 8279.25 microstrain-meters, with a CV of 6.8%. This variability can be attributed to two primary factors:

a) Despite having the same number of axles, trucks differ in overall configuration, length, and operational function, leading to substantial differences in gross vehicle weights.
b) The degree of loading varies across the truck population, with some vehicles potentially operating at partial load capacity.

Although the observed level of repeatability may be adequate for preliminary evaluations where high accuracy is not critical, achieving more consistent results requires a more meticulous selection of vehicle types. Additional criteria such as axle spacing uniformity and vehicle functionality should be considered to minimize variability. To demonstrate this, Figure 4 presents sample images of log trucks, alongside their corresponding strain responses, collected during the same time period (June 2024). A total of 10 isolated log truck events were identified.

Figure 4. 7-Axle log trucks isolated in June 2024: sample truck photos (a), girder strain response (b)

(a)

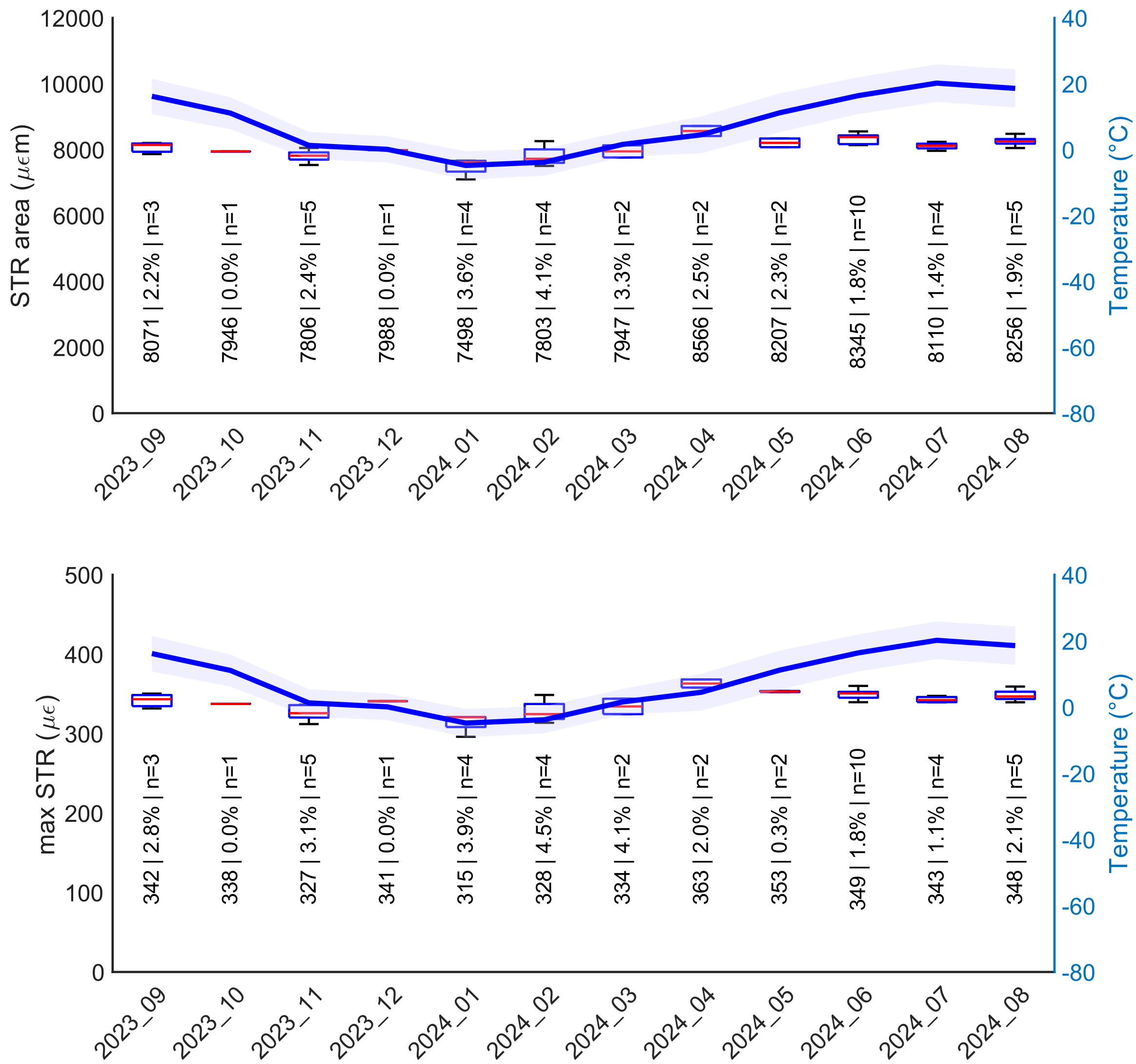


(b)

The analysis revealed that log trucks exhibited an average maximum strain of 349.41 microstrains (CV = 1.8%) and an average strain area of 8344.54 microstrain-meters (CV = 1.8%). Unlike the general 7-axle truck class, the log trucks showed significantly lower variability. This can be attributed to the vehicles' highly similar configurations and their specialized function of transporting logs, likely subject to standardized loading practices or operational guidelines.

Figure 5 displays the distribution of log truck strain responses over a one-year monitoring period, along with monthly average temperature data from the nearest Environment Canada climate station.

Figure 5. Spread of strain response data for log trucks over a year, along with temperature data



The results confirm that carefully selecting vehicle classes—considering both configuration and operational characteristics—can yield highly repeatable strain responses over extended monitoring periods. Consequently, such meticulous selection enhances the robustness and reliability of bridge structural monitoring efforts.

Temperature Dependency

Given the long-term nature of the monitoring, it was hypothesized that environmental conditions, particularly ambient temperature, could influence the observed strain responses. To evaluate the potential relationship between temperature and strain measurements, Pearson correlation analysis was conducted.

The Pearson correlation coefficient quantifies the strength and direction of the linear association between two continuous variables, assuming approximate normality and linearity. Coefficient values near +1 or –1 indicate strong positive or negative relationships, respectively, while values near zero suggest little or no linear association. In this study, correlation coefficients were calculated between monthly average temperatures and two key response metrics:

- Area under the strain curve (STR area), and
- Maximum strain (Max STR).

The resulting correlation coefficients were 0.601 (STR area vs. average temperature) and 0.588 (Max STR vs. average temperature), indicating a moderate and statistically significant positive linear relationship. These results suggest that as the ambient temperature increases, the measured strain responses also tend to increase. Therefore, when comparing bridge response data collected at different times of the year, temperature effects must be carefully considered. Further correction or compensation procedures should be applied to ensure that seasonal variations in environmental conditions do not confound the interpretation of structural performance trends.

Conclusion

This study demonstrated the feasibility of leveraging raw measurement data from Bridge Weigh-In-Motion (BWIM) systems to monitor the long-term structural behavior of highway bridges. Using one year of continuous traffic data collected from a bridge on the TransCanada Highway in New Brunswick, it was shown that specific classes of vehicles—identified solely through structural response data without requiring prior knowledge of their weights—can be effectively utilized for structural monitoring purposes.

The selection of appropriate vehicle types was found to be critical, with more consistent configurations (such as specialized log trucks) yielding significantly lower variability in observed strain responses. This highlights the importance of vehicle class selection based on the desired accuracy and repeatability of the monitoring objectives.

Additionally, the results revealed that ambient temperature changes exhibit a moderate, statistically significant correlation with structural response parameters. This finding emphasizes that variations in measured strain are not necessarily indicative of structural deterioration and that environmental factors must be carefully accounted for in long-term monitoring analyses.

Overall, the results suggest that BWIM systems, when combined with strategic vehicle selection and appropriate environmental corrections, offer a promising, low-cost pathway for continuous structural health monitoring of bridges. Future work may explore the incorporation of temperature compensation models and the extension of this methodology to different traffic scenarios and environmental conditions.

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